

When more of the same is better

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Problem solving (e.g., drug design, traffic engineering, software development) by task forces represents a substantial portion of the economy of developed countries. Here we use an agent-based model of cooperative problem solving systems to study the influence of diversity on the performance of a task force. We assume that agents cooperate by exchanging information on their partial success and use that information to imitate the more successful agent in the system – the model. The agents differ only in their propensities to copy the model. We find that, for easy tasks, the optimal organization is a homogeneous system composed of agents with the highest possible copy propensities. For difficult tasks, we find that diversity can prevent the system from being trapped in sub-optimal solutions. However, when the system size is adjusted to maximize performance the homogeneous systems outperform the heterogeneous systems, i.e., for optimal performance, sameness should be preferred to diversity.

I. INTRODUCTION

Understanding the factors that influence the capability of a group of individuals to solve problems is a central issue on collective intelligence [1–3] and on organizational design [4–6], nonetheless the meager interchange of ideas between these two research areas. Conventional wisdom says that a group of cooperating individuals can solve a problem faster than the same group of individuals working in isolation, and that the higher the diversity of the group members, the better the performance. Although there has been some progress on the quantitative understanding of the factors that make cooperative group work effective [2, 7, 8], only very recently a workable minimal agent-based model of distributed cooperative problem solving system was proposed [3] (see also [5]). Here we build on that model to dispute some common-sense views of the benefits of diversity in group organization.

We consider a distributed cooperative problem solving system in which agents cooperate by broadcasting messages informing on their partial success towards the completion of the goal and use this information to imitate the more successful agent (model) in the system. In doing so, we follow Bloom in conferring imitative learning the central role in the emergence of collective intelligence: “Imitative learning acts like a synapse, allowing information to leap the gap from one creature to another” [9]. The parameters of the model are the number of agents in the system L and the copy or imitation propensities $p_a \in [0, 1]$ of agent $a = 1, \dots, L$. Previous analyses have considered the homogeneous case only, $p_a = p \forall a$ [3, 10]. Here we focus on the case that the copy propensities are random variables instead, and measure the system performance by the time t^* the system requires to find the solution of the task.

We find that endowing the agents with different copy propensities can greatly reduce the chances that the system is temporarily trapped in sub-optimal solutions (local maxima), which is a very likely outcome of the imitative search for large homogeneous systems [3, 10]. How-

ever, in the regime of system sizes where that search strategy is more effective than the independent search, diversity impairs the system performance and the optimal performance is achieved by the homogeneous system.

II. THE TASK

The task posed to the agents is to find the unique global maximum of a fitness landscape generated using Kauffman’s NK model [11]. This model allows the tuning of the ruggedness of the landscape – and hence of the difficulty of the task – by changing the integer parameters N and K . More pointedly, the NK landscape is defined in the space of binary strings of length N and so this parameter determines the size of the solution space, namely, 2^N . The other parameter $K = 0, \dots, N - 1$ is the degree of epistasis that has a direct influence on the number of local maxima on the landscape. In particular, for $K = 0$ the (smooth) landscape has a single maximum, whereas for $K = N - 1$, the (uncorrelated) landscape has on the average $2^N / (N + 1)$ maxima with respect to single bit flips and the NK model reduces to the Random Energy model [12].

The NK model associates a fitness value $\Phi(\mathbf{x})$ to each binary string $\mathbf{x} = (x_1, x_2, \dots, x_N)$, with $x_i = 0, 1$, which is given by an average of the contributions from each entry of the string, i.e.,

$$\Phi(\mathbf{x}) = \frac{1}{N} \sum_{i=1}^N \phi_i(\mathbf{x}), \quad (1)$$

where ϕ_i is the contribution of entry i to the fitness of the string \mathbf{x} . The quantity ϕ_i depends on the state x_i as well as on the states of the K right neighbors of i , i.e., $\phi_i = \phi_i(x_i, x_{i+1}, \dots, x_{i+K})$ with the arithmetic in the subscripts done modulo N . This is the reason the parameter K is known as the degree of epistasis: it measures the degree of interaction (epistasis) among entries of the strings. In addition, we assign to each ϕ_i a uniformly distributed random number in the unit interval

[11], which guarantees that $\Phi \in (0, 1)$ has a unique global maximum. Finding this maximum for $K > 0$ is a NP-complete problem [13], which means that the time required to solve the problem using any currently known deterministic algorithm increases exponentially fast with the length N of the strings [14]. For $K = 0$ the sole maximum of Φ is easily located by picking for each entry i the state $x_i = 0$ if $\phi_i(0) > \phi_i(1)$ or the state $x_i = 1$, otherwise. Finally, we note that the correlation between the fitness of any two neighboring configurations (i.e., configurations that differ by a single entry) is $\text{corr}(\Phi(\mathbf{x}^a), \Phi(\mathbf{x}^b)) = 1 - (K + 1)/N$, where $\mathbf{x}^a = (x_1, \dots, x_i, \dots, x_N)$ and $\mathbf{x}^b = (x_1, \dots, 1 - x_i, \dots, x_N)$, regardless of the value of the entry i .

III. THE AGENTS

We consider a system composed of L agents and assume that each agent can interact with all the others (see [15] for the study of more complex connection patterns). Each agent operates in an initial binary string drawn at random with equal probability for the bits 0 and 1. At any trial t , agent a can choose between two distinct processes to operate on its associated string.

The first process, which happens with probability $1 - p_a$, is a random, exploratory move in the solution space that consists of flipping a single randomly selected bit of the binary string. The second process, which happens with probability p_a , is the imitation of a model string, i.e., the string with the highest fitness value among the L strings at the trial. The imitation or copy process is implemented as follows. First the target string a is compared with the model string m and the different bits are singled out. Then the agent selects at random one of the distinct bits and flips it so that this bit is now the same in both strings. As a result of the imitation process the target string becomes more similar to the model string. In the case the string a is identical to the model string, the agent executes the exploratory move with probability one.

The imitation procedure was motivated by the mechanism used to simulate the influence of an external media [16, 17] in the celebrated agent-based model proposed by Axelrod to study the process of culture dissemination [18]. This procedure sets our model apart from a similar model studied in the Management and Organizations literature [5] (see also [6]) where the imitation mechanism is such that the target string becomes identical to the model string after imitation. This non-incremental change may permanently stuck the search in a local maximum. In that context, the exploratory move is called exploration, since the agent may generate new information, and the copying process, exploitation, since the agent uses information that is already present in the system [19].

The parameter $p_a \in [0, 1]$ is the imitation or copy propensity of agent a . If $p_a = 0$ then agent a will explore the solution space independently of the other agents. In

previous studies of this model [3, 10, 15] we assumed that the L agents exhibited the same imitation behavior, i.e., $p_a = p$ for $a = 1, \dots, L$. Here we introduce variety in the behavior of the agents by endowing them with different copy propensities. In particular, we consider the case that the p_a 's are identically distributed independent random variables drawn from the uniform probability distribution $Q_U(p_a) = 1$ for $p_a \in [0, 1]$ and $Q_U(p_a) = 0$ otherwise, as well as the case that they are drawn from the trimodal distribution

$$Q_T(p_a) = \frac{1}{3}\delta(p_a) + \frac{1}{3}\delta(p_a - 1/2) + \frac{1}{3}\delta(p_a - 1). \quad (2)$$

Since in both cases we have $\langle p_a \rangle = 1/2$, a suitable homogeneous system that can serve as standard for gauging the benefits of diversity is that for which $p_a = 1/2$ for $a = 1, \dots, L$. We note that in the case of the trimodal distribution we consider only realizations which exhibit all the three different values of the copy propensities, regardless of their proportions.

The search ends only when one of the agents finds the global maximum and we denote by t^* the number of trials made by the agent that found the solution. Since the trial number t is incremented by one unit when the L agents have executed one of the two operations on its associated string, t^* stands also for the number of trials made by any one of the L agents in the system. Hence the total number of agent updates necessary to find the global maximum is Lt^* and so the computational cost of the search can be defined as $C \equiv Lt^*/2^N$, where for convenience we have rescaled t^* by the size of the solution space 2^N . We note that the update of the L agents in a trial is sequential and so the model strings may change several times within the same trial.

IV. THE SIMULATIONS

Since the complexity of the task is a key element to be considered when determining the organization that maximizes the problem-solving performance of the system [5, 6], we study imitative searches on easy tasks, i.e., smooth NK landscapes with a single maximum ($K = 0$), and on more difficult tasks, i.e., rugged NK landscapes characterized by the parameters ($N = 12, K = 3$) and ($N = 18, K = 5$). For each realization of a fitness landscape we carry out 10^5 searches starting from different initial conditions (initial strings and copy-propensity realizations) and the averaged results are then averaged again over at least 10^3 realizations of landscapes characterized by the same values of the parameters N and $K > 0$. In the case $K = 0$ all landscapes are equivalent and so we do not need to average over different realizations.

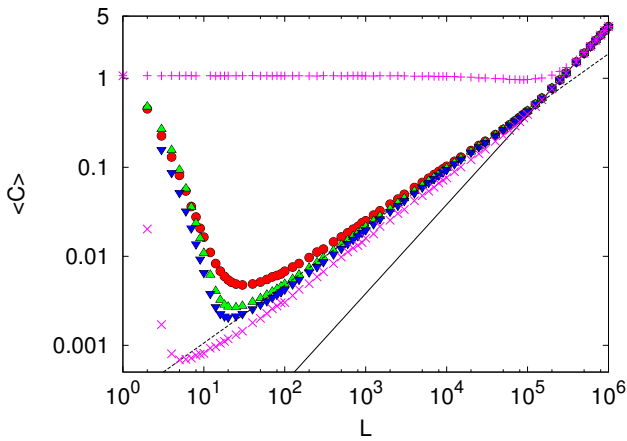


FIG. 1: (Color online) Mean computational cost $\langle C \rangle$ as function of the system size L for a system of identical agents with $p_a = 0.5 \forall a$ (●), a system of agents with p_a uniformly distributed in the unit interval (▲), and a system of agents with p_a generated using a trimodal distribution (▼). The symbols (+) are the results for the independent search ($p_a = 0 \forall a$) and the symbols (x) for the imitative search with $p_a = 1 \forall a$. The solid line is the linear function $\langle C \rangle = L/2^{18}$, and the dashed line is the fitting $\langle C \rangle = 0.79 (L/2^{18})^{0.65}$ of the uniform distribution data in the range $L \in [10^3, 10^5]$. The parameters of the smooth NK landscape are $N = 18$ and $K = 0$.

A. Smooth Landscapes

In Fig. 1 we show the performances, as measured by the mean computational cost $\langle C \rangle$, of a system composed of identical agents (i.e., $p_a = 0.5$ for all agents), a system composed of agents with p_a drawn from the uniform distribution $Q_U(p_a)$ and a system of agents with p_a drawn from the (biased) trimodal distribution $Q_T(p_a)$. As observed in previous analyses of the imitative search [3, 10, 15], for each condition there is a system size at which the computational cost is minimum. We note that, for a landscape without local maxima, the best performance of the imitative search is achieved by setting $p_a = 1$ for all agents (see Fig. 1), since copying the fittest string at the trial is always a certain step towards the solution of the problem [10]. This is the reason the trimodal distribution gives the best performance among the three distributions with $\langle p_a \rangle = 0.5$ exhibited in Fig. 1: it simply produces systems with a large proportion of experts (i.e., agents with $p_a = 1$). In fact, we have verified that a bimodal distribution, in which half of the agents have $p_a = 0$ and the other half $p_a = 1$, yields a better performance than the trimodal distribution.

For L greater than the optimal system size, we observe two distinct growth regimes of the computational cost. The first regime, which occurs for $L < 2^N$ and holds over for nearly three decades for the data of Fig. 1, is characterized by a sublinear growth $\langle C \rangle \sim L^\alpha$ with $\alpha < 1$ and signals a scenario of mild negative synergy

among the agents since the time t^* necessary to find the global maximum decreases with $L^{\alpha-1}$ rather than with L^{-1} as in the case of the independent search (absence of synergy). Although this regime is important because for large N it is the only growth regime that can be observed in the simulations, the specific value of the exponent α is not very informative since it depends on the distribution of the copy propensities (see Fig. 1) and it increases with increasing N . For instance, for the uniform distribution we found $\alpha \approx 0.51$ for $N = 12$, $\alpha \approx 0.65$ for $N = 18$ and $\alpha \approx 0.72$ for $N = 22$. The second regime, which takes place for $L > 2^N$, is described by the linear function $\langle C \rangle = L/2^N$ and corresponds to the situation where the system size is so large that the solution is found in the first trials. In this regime, t^* is not affected by the value of L , i.e., adding more agents to the system does not decrease the time required to find the solution. Finally, we note that for $K = 0$ the imitative search always performs better than the independent search.

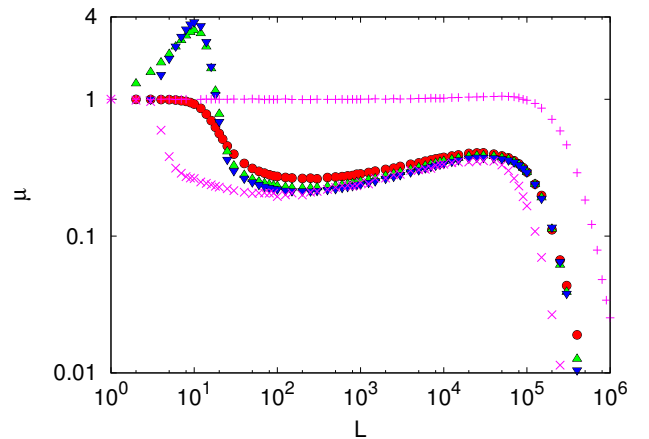


FIG. 2: (Color online) Ratio μ between the standard deviation of the computational cost and its mean value as function of the system size L for the different system compositions shown in Fig. 1. The symbols convention and the parameters of the NK landscape are the same as for that figure.

It is also instructive to consider the ratio between the standard deviation of the computational cost and its mean value, i.e., $\mu = [\langle C^2 \rangle / \langle C \rangle^2 - 1]^{1/2}$, which is shown in Fig. 2. Clearly, μ also gives the ratio between the standard deviation of the time required to find the global maximum t^* and its mean value. In the regime that $\mu \approx 1$, the distribution of the computational cost can be well described by an exponential distribution, though we note that the correct distribution in the case of the independent search is the geometric distribution [15]. The high dispersion observed for small size heterogeneous systems is due to the great dispersion of the system composition, a factor whose effect decreases as L increases. We recall that this effect is absent for $L = 3$ in the case the propensities are generated by the trimodal distribution because we consider only realizations where the three

classes are represented in the system. This effect aside, it was expected that the dispersion of t^* would be smaller than for the independent search: given the smoothness and non-degeneracy of the landscape, the searches should follow neighboring paths in the solution space. It is interesting that although the search strategies exhibit the same mean computational cost in the regime $L \gg 2^N$, the imitative search has a much smaller dispersion than the independent search.

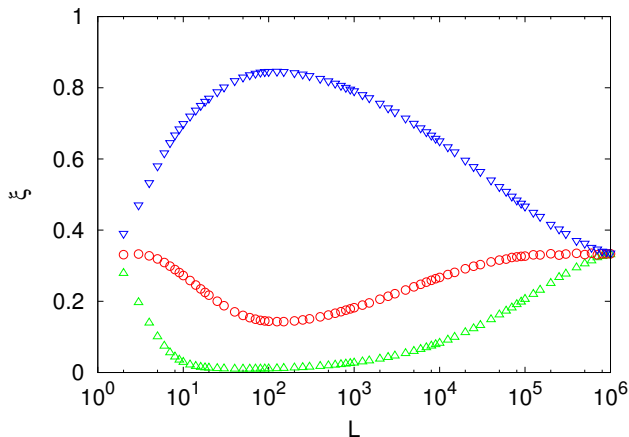


FIG. 3: (Color online) Fraction of the searches for which the global maximum was found by agents with low-copy (\triangle), average-copy (\circ) and high-copy (∇) propensities for the case p_a is uniformly distributed in the unit interval. The parameters of the smooth NK landscape are $N = 18$ and $K = 0$.

An interesting issue that we can address in the case of heterogeneous systems is whether there is a correlation between the propensity of an agent to imitate p_a and its chances of finding the global maximum. To treat this issue for the case the propensities are generated by the uniform distribution $Q_U(p_a)$ we divide the agents in three classes, namely, low-copy propensity agents characterized by $p_a \in [0, 1/3)$, average-copy propensity agents for which $p_a \in [1/3, 2/3)$ and high-copy propensity agents for which $p_a \in [2/3, 1]$. Figure 3 shows the probability ξ that an agent belonging to one of those classes hits the global maximum. This figure corroborates our preceding remark that for a smooth landscape the best strategy for the agents is to copy the model string, since that string always displays faithful information about the location of the global maximum. For $L > 2^N$ the determining factor for an agent to hit the solution is its proximity to the global maximum when the initial strings are set randomly and so all copy propensity classes perform equally in this regime, as expected. The results for the trimodal distribution $Q_T(p_a)$ are qualitatively the same as those shown in Fig. 3, except that the high-copy propensity class, which in this case is characterized by $p_a = 1$, has a slightly higher probability of finding the global maximum than it has for the uniform distribution.

B. Rugged Landscapes

The study of the performance of the imitative search on rugged landscapes is way more compute-intensive than on smooth landscapes for two reasons: first, the number of trials t^* to hit the solution for system sizes near the optimal size is about 100 times greater than for smooth landscapes. Second, now we need to average the results over many (at least, 10^3) realizations of the NK landscape. Hence to grasp the behavior of the system in all regimes of L studied before, we will consider first a rather small landscape with parameters ($N = 12, K = 3$) and then verify whether the results hold true for a larger landscape with parameters ($N = 18, K = 5$). Note that for both landscapes the correlation between the fitness of neighboring strings is $2/3$.

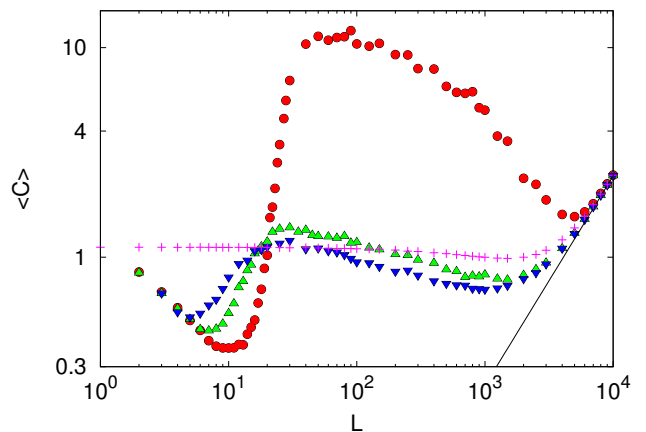


FIG. 4: (Color online) Mean computational cost $\langle C \rangle$ as function of the system size L for a system of identical agents with $p_a = 0.5 \forall a$ (\bullet), a system of agents with p_a uniformly distributed in the unit interval (\blacktriangle), and a system of agents with p_a generated using a trimodal distribution (\blacktriangledown). The symbols (+) are the results for the independent search $p_a = 0 \forall a$. The solid line is the linear function $\langle C \rangle = L/2^{12}$. The parameters of the rugged NK landscape are $N = 12$ and $K = 3$.

Figure 4 summarizes our results for the NK landscape with parameters ($N = 12, K = 3$). This figure reveals that moderately large (i.e., $L \in [20, 2000]$) homogeneous systems can easily be trapped by the local maxima, from which escape can be extremely costly. This is akin to the groupthink phenomenon [20], when everyone in a group starts thinking alike, which can occur when people put unlimited faith in a talented leader (the model strings, in our case). The finding that these traps can be circumvented by endowing the agents with different parameters of the behavioral rules is a main thrust of the arguments pro diversity to boost system performance [4]. Our results corroborate that viewpoint since the heterogeneous systems exhibit an overall performance slightly superior to the independent search, which, we recall, is not affected by the presence or absence of local maxima. The

surprising finding, however, is that for small system sizes, where the imitative search can be said to be efficient in the sense that t^* decreases superlinearly with increasing L [1, 2], the homogeneous system performs best.

The properly rescaled deviations around the mean values of the computational cost are shown in Fig. 5. As opposed to the results for the smooth landscape (see Fig. 2), the deviations now are larger than those for the independent search for almost all values of L . The reason is that the searches that are (temporarily) trapped by local maxima contribute with very large costs, whereas the searches that avoid those traps can reach the global maximum very quickly. We note that μ does not account for fluctuations of the computational cost due to the different landscape realizations: the standard deviation as well as the mean of the computational cost are measured for each landscape realization and then their ratio is averaged over the different realizations.

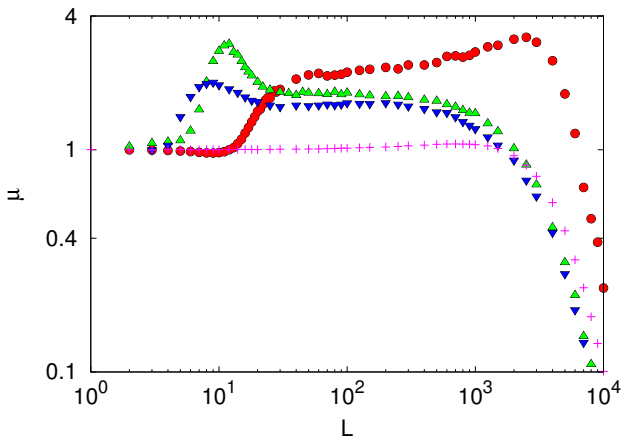


FIG. 5: (Color online) Ratio μ between the standard deviation of the computational cost and its mean value as function of the system size L for the different system compositions shown in Fig. 4. The symbols convention and the parameters of the NK landscape are the same as for that figure.

The chances that agents belonging to the low-copy, average-copy or high-copy propensity classes hit the global maximum are shown in Fig. 6 in the case p_a is drawn from the uniform distribution $Q_U(p_a)$. The situation now is way more complex than for the smooth landscape. In this case the minimum cost occurs for $L = 7$, which coincides with the system size at which the probability that an agent in the high-copy class hits the solution is maximum. Interestingly, the agents in the low-copy class are the most likely to hit the solution in the region where the imitative search is outperformed by the independent search, i.e., for the values of L where the system seems to be more susceptible to the presence of the local maxima. The results are qualitatively the same for the trimodal distribution.

The average performance of the imitative search on rugged landscapes characterized by the parameters

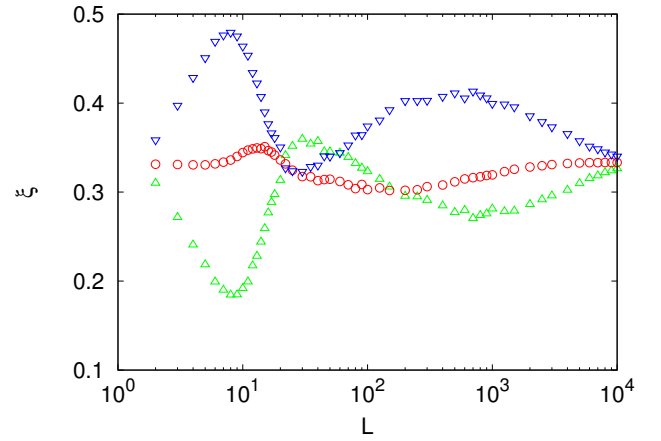


FIG. 6: (Color online) Fraction of the searches for which the global maximum was found by agents with low-copy (Δ), average-copy (\circ) and high-copy (∇) propensities for the case p_a is uniformly distributed in the unit interval. The parameters of the rugged NK landscape are $N = 12$ and $K = 3$.

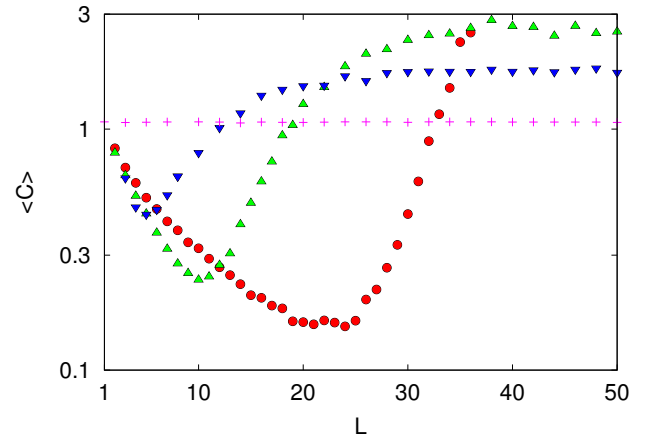


FIG. 7: (Color online) Mean computational cost $\langle C \rangle$ as function of the system size L for a system of identical agents with $p_a = 0.5 \forall a$ (\bullet), a system of agents with p_a uniformly distributed in the unit interval (\blacktriangle), and a system of agents with p_a generated using a trimodal distribution (\blacktriangledown). The symbols (+) are the results for the independent search $p_a = 0 \forall a$. The parameters of the rugged NK landscapes are $N = 18$ and $K = 5$.

($N = 18, K = 5$) is shown in Fig. 7 for small system sizes. These results are qualitatively the same as those shown in Fig. 4, except that a tendency that is barely visible in that figure becomes evident now: the heterogeneous systems exhibit the best performance for very small ($L < 10$) system sizes. Nevertheless, the advantage of the homogeneous system is striking for sizes in the range $L \in [10, 30]$, corroborating the puzzling finding that if the system size can be adjusted to maximize performance then the homogeneous system performs better than the heterogeneous

one, given the constraint that $\langle p_a \rangle$ is the same in all conditions. The results regarding the dispersion around the mean computational cost and the chances of agents in the different copy propensity classes to hit the solution are qualitatively the same as those discussed for the landscapes with parameters ($N = 12, K = 3$).

Finally, we note that since finding the global maxima of NK landscapes with $K > 0$ is an NP-Complete problem [13], one should not expect that the imitative search (or any other search strategy, for that matter) would find those maxima much more rapidly than the independent search.

V. CONCLUSION

Our findings corroborate, in part, the prevalent views on the effects of diversity on the efficiency of cooperative problem-solving systems [4]. In particular, in the case of easy tasks, modeled here by smooth landscapes without local maxima, for which there is an optimal imitation strategy, the best performance is achieved by a homogeneous system of agents equipped with that strategy, the so-called experts (see Fig. 1). In the case of difficult tasks, modeled by landscapes plagued of local maxima, we find that diversity is a palliative for the main deficiency of the imitative search strategy, namely, the lure of the model strings in the vicinity of the local maxima, a phenomenon analogous to Groupthink [20]. In fact,

for some system sizes diversity may produce a more than tenfold decrease of the computational cost in comparison with that of homogeneous systems. We note, however, that a more efficient strategy to bypass Groupthink is to reduce the influence of the model string by decreasing the connectivity of the network [15].

The main result of this paper is the surprising finding that if one is allowed to adjust the system size L to maximize the performance, then the homogeneous system will outperform the heterogeneous ones. To offer a clue to understand this finding, we note that the optimal size of the homogeneous system is $L^* \approx N$ (see Figs. 1, 4 and 7), which means that the optimal system is composed of a model string together with a cloud of mutant strings that differ from it typically by one or two entries. Since this is the manner viral quasispecies explore their fitness landscapes [21], it is probably the optimal (or near-optimal) way to explore rugged fitness landscapes.

Acknowledgments

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